8. BÖLÜM / CHAPTER 8

CO_2 EMISSION, ENERGY CONSUMPTION AND ECONOMIC GROWTH IN BRICS COUNTRIES: EVIDENCE FROM CROSS-SECTION DEPENDENCE AND STRUCTURAL BREAKS

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ABSTRACT

In the last three decades, the effects of economic activites on CO_2 emissions have become a very significant topic. Several researchers have focused on energy consumption and economic growth in the context of environmental degradation, both at the national and international level. Three of the world's top five CO_2 emitters are part of the BRICS, which is a group consisting of five emerging countries. This study re-examines the relationship between energy consumption, economic growth, and CO_2 emissions, as well as the Kuznets Environmental Curve (EKC) hypothesis, in the BRICS countries (i.e., Brazil, Russia, India, China, and South Africa) during the period of 1971–2013 through a recently introduced panel cointegration technique that allows for cross-section dependence and structural breaks. The results reveal a cointegration relationship among the variables, and the long-run coefficients show that an increase in energy consumption and economic growth increases CO_2 emissions. The results show that there is an inverse U-shaped relationship between economic growth and carbon dioxide emissions and confirm the validity of the Environmental Kuznets Curve hypothesis for BRICS countries.

Keywords: CO_2 emission, Environmental Kuznets Curve (EKC), Panel data, cross-section dependence, structural breaks, BRICS countries

1. Introduction

The increase in global warming and climate change is one of the most important issues that keeps the world agenda busy and is an ongoing concern. One of the underlying causes of climate change is the increased concentration of greenhouse gases (GHGs) due to anthropogenic activity. In particular, fossil fuel energy related to carbon dioxide emissions (CO_2) account for more than two thirds of the five kinds (water vapor -H_2O, carbon dioxide -CO_2, methane -CH_4, nitrous oxide -N_2O, and ozone -O_3) of primary greenhouse gas emissions likely associated with climate change. The Intergovernmental Panel on Climate Change (IPCC) shows that greenhouse gas emissions increased by 1.6% year-to-year while major CO_2 emissions from fossil fuels have increased by 1.9 % in the last three years. Environmental degradation caused by greenhouse gas emissions have had a widespread effect on the quality of human life, natural systems, and economic performance.

Since it has been recognized by policy makers that climate change is a global problem and requires international cooperation, governments have also paid more attention to and have made more effort in international cooperation over the last three decades. The IPCC (1995) announced that CO_2 emission, which is largely produced by human activities due to development and industrialization over the last decades, causes global climate change. Economic development mainly depends on energy consumption; thus, economic activity and energy usage are the factors driving GHG emissions to increase. The 1997 Kyoto Protocol had the goal of reducing greenhouse gases that cause climate change. The first initiative on global climate change was the Paris Agreement of 195 countries, which was signed in 2015. As a long-term objective, governments have agreed to keep the average global temperature rise at 2°C below the pre-industrial level and to reduce the risks and impact of climate change to 1.5°C. The increase in CO_2 emissions and other pollutants is also associated with high energy consumption due to increasing population growth as well as economic development (Cropper and Griffiths, 1994). Population increases lead to an increase in energy consumption connected with industry, transportation, and power, which consequently promotes pollution and leads to seriously environmental pollution.

The IPCC (2015) has repeated that globally, economic and population growth continue to be the most significant drivers of the increase of CO_2 emissions from fossil fuel combustion. According to this report, the contribution of population growth between 2000-2010 remained roungly identical to the previous three decades while the contribution of growth has risen sharply and, without additional efforts to reduce GHG emissions beyond those in place today, emissions growth is expected to persist, driven by growth in the global population and economic activities.

Therefore, the control of carbon emissions in the context of environmental pollution has a great importance, and developed and developing countries have concentrated their attention on this issue. Because of that, the relationship between environmental degradation and its causes has been the subject of scientific research since the start of the 1990s. Many scholars have discussed the relationship between economic growth, energy consumption, and CO_2 emissions from the perspective of qualitative and quantative techniques, using time series, cross section, and panel data for single countries (see, e.g., Sinha and Shahbaz, 2018 (India); Esteve and Tamarit, 2012 (Spain); Fosten et al., 2012 (UK); Piaggio et al., 2017 (Uruguay); Sugiawan and Mangi, 2016 (Indonesia), Wang et al, 2011 (China), Atasoy, 2017 (US), Farhani et al, 2014 (Tunisia), Al- Mulali et al. 2016 (Kenya), Ozturk and Al-Mulali 2015 (Combodia)) and/or groups of countries (see, e.g., Wang and Zhang, 2020 (BRICS) Churchill et al., 2018 (OECD), Maryam et al., 2017 (BRICS), Zoundi, 2017 (ASEAN), Arouri et.al. 2012 (MENA), Apergis and Payne 2009 (Central America)).

In this context, since the pioneering studies of Grossman and Krueger (1993, 1995) and Panayotou (1993) to the present day, the relationship between economic development and environmental degradation, which is illustrated by the so-called Environmental Kuznets Curve (EKC) hypothesis, has become the most important research issue for researchers and policy makers working in these fields. According to this hypothesis, economic growth causes CO_2 emissions and therefore environmental degradation in the early stage of economic development because of the scale effect. However, as economies reach higher levels, emissions will be reduced due to the *composition* effect, thereby improving environmental quality. Thus, an inverted U-shaped relationship exists between environmental degradation and economic activity since a further increase in income per capita leads to lower emissions.

The relationship between environmental degradation (per capita) and income (per capita) described above is shown in Fig. 1 and is similar to the original curve proposed by Simon Kuznets (1955) concerning the relationship between income inequality and economic growth.

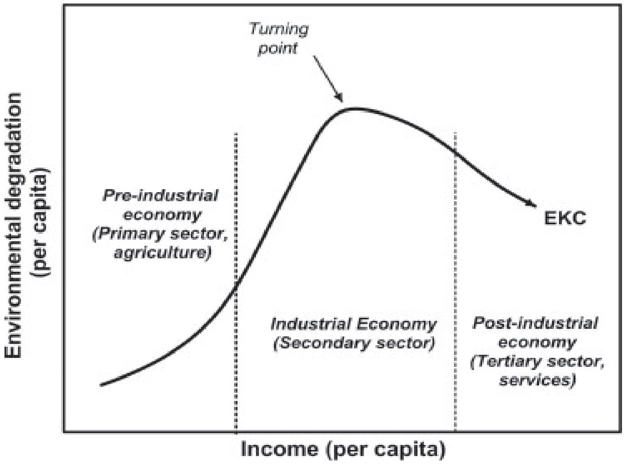

Figure 1. An Environmental Kuznets Curve (EKC)

In particular, the BRICS countries (i.e., Brazil, Russia, India, China, and South Africa), which are large and emerging economies, are attributed for an increasingly important share of the growth of the global economy and energy consumption in the last three decades. The gross domestic product (GDP) in the BRICS countries, which hold more than 40% of the world's population, has risen dramatically from \$2,187 billion US (constant 2010 US\$) in 1985 to \$16,266 billion US in 2016, with an average annual growth rate of 6.5%. According to Pao and Tsai (2010), the GDP of BRICS countries is expected to be larger than that of the G7's, which are the seven largest developed economies (i.e., USA, Canada, UK, Germany, France, Italy, and Japan). However, the rapid economic development of the BRICS countries has also brought along a number of severe environmental problems, particularly carbon dioxide (CO_2) emissions.

Table 1
Carbon emission of the BRICS countries in 2017

Region	**Annual carbon emission ($Mt\ CO_2$)**	**% of world emission**	**Rank in the world**
World	37,077.404	100	
China	10,877.218	29.34	1
Russia	1,764.866	4.76	4
Brazil	492.791	1.33	15
South Africa	467.654	1.26	16
India	2,454.774	6.62	3
Source: PBI Netherlands Environmental Assessment Agency (2018).			

According to statistics from the PBI, presented in Table 1, three of the world's top five CO_2 emitters are BRICS countries. CO_2 emissions of the BRICS countries have reached 16,057 million tons (mt) in 2017 and have emitted over 43 % of world carbon emissions. For this reason, many scientists working on environmental degradation, including the issues of global warming and climatic instability, have directed their research to the BRICS countries, as individual countries or the group as a whole. Specifically, China is the world's second-largest economy and the biggest global CO_2 emission emitter. While the pace of the three major economies (USA, Japan, European Union) has slowed down since 2000, the Chinese economy, which is the largest economy in the BRICS, has started to develop rapidly. However, this has led to the burning of a large number of fossil fuels and an increase in total carbon emissions.

This study re-investigates the relationship between economic growth, energy consumption, and carbon emissions in the BRICS countries over the period of 1971-2013. The study is expected to contribute to the literature at the following points. In this study, panel cointegration techniques were used, which take into account cross-section dependence and structural breaks.

The remainder of this study is organized as follows: Section 2 gives a brief overview of the related literature, the data and EKC model is introduced in Section 3, Section 4 proposes the econometric methodology, and the results of the empirical analysis are presented in Section 5.

2. Brief overview of the literature

Since the pioneering work of Kraft and Kraft (1978), which investigated the possible causal links between energy consumption and economic growth, this issue has become a hot topic in environmental science and energy economics. Also, regarding the carbon emissions of the BRICS countries, several scholars have applied different econometric methods to explore the impacts on environmental degradation of different determinant variables, such as urbanization, electricity consumption, renewable energy, FDI, and natural gas consumption. The following literature has shown extensive interest in the various relationships with levels of CO_2 emissions, which are frequently used as a measure of environmental pollution and economic growth. The studies for BRICS countries in the literature are as follows:

Chousa et al. (2008) examined whether economic and financial development along with energy consumption tend to increase environmental damage or not and the validity of the environmental Kuznets curve for BRIC (Brazil, Russia, India, China) countries during the period of 1992-2004. The results obtained using the standard reduced-form modeling approach form show that increased energy consumption due to economic growth leads to an increase in

CO_2 emissions and empirically confirms the EKC existence in BRIC countries. Tamazian et al. (2009) investigated the relationship between economic development and carbon emissions by adding financial development in BRIC countries during the period of 1992-2004. The results of the study using panel data show that both economic and financial development are determinants of environmental quality, that EKC is valid in BRIC economies, and that higher degree of economic and financial development decreases environmental degradation.

Pao and Tsai (2010) presented dynamic causal relationships between pollutant emissions, energy consumption, and output for BRIC countries by using a panel cointegration technique for the period of 1971–2005, with the exception for Russia, which was during the period of 1990–2005. According to the results, in long-run equilibrium, energy consumption had a positive and statistically significant effect on emissions while real output exhibited the inverted U-shape pattern associated with the Environmental Kuznets Curve (EKC) hypothesis. The panel causality results also indicated there were an energy consumption–emissions bidirectional strong causality and an energy consumption–output bidirectional long-run causality, along with both unidirectional strong and short-run causalities from emissions and energy consumption, respectively, to output. Pao and Tsai (2011), in their second study, which included Foreign Direct Investment (FDI) as a fourth variable, examined the impact of both economic growth and financial development on environmental degradation, using a panel cointegration technique for the period between 1980 and 2007, with the exception for Russia, whose period was 1992–2007. In long-run equilibrium, CO_2 emissions appeared to be energy consumption elastic and FDI inelastic, and the results seemed to support the Environmental Kuznets Curve (EKC) hypothesis. The causality results indicated that there existed a strong bidirectional causality between emissions and FDI and an unidirectional strong causality running from output to FDI.

Mehrara and Ali Rezaei (2013) investigated, using panel data method, the relationship between carbon emissions, trade liberalization, and economic growth in the context of the EKC during the span of 1960-1996 for BRICS countries. Their findings supported an inverted U-shape pattern associated with the Environmental Kuznets Curve (EKC) hypothesis for the BRICS region. Bakirtas et al. (2014) described the relationship between carbon emission and income for the period of 1990-2010 for 34 OECD and BRICS countries. The results showed that there was a statistically significant relationship between income and carbon emission in the long-run.

Cowan et al. (2014) applied a bootstrap panel causality methodology, accounting for dependency and heterogeneity across countries, to explore the causal effect of electricity consumption on carbon emissions in the BRICS countries for the period of 1990–2010.

The results of the panel bootstrap method suggested that the existence and direction of the Granger causality differed among the different BRICS countries. Chang (2015) investigated the relationship between carbon emission and different energy variables for G7 and BRICS countries, based on the analysis of energy efficiency and environmental Kuznets curves. The data period was from 2000 to 2010. According to the results, the EKC hypothesis was valid in BRICS countries

Wang et al. (2016) analyzed the relationship between urbanization and carbon emissions, applying the panel Granger causality method for the 1985–2014 period in BRICS countries. Empirical results clearly indicated that in the long term, urbanization was the Granger cause of carbon emission. Sinha and Sen (2016) investigated, following a generalized method of moments (GMM) technique, the validity of the EKC hypothesis in BRIC countries for the period of 1980-2013. The results indicated that bidirectional causality existed between CO_2 emissions and economic growth as well as the existence of Environmental Kuznets curve. Tedino (2017) studied the environmental impact of economic growth in BRICS countries for the period of 1992-2012. According to the results, the EKC hypothesis was valid in China, India, and South Africa, but the EKC hypothesis was not valid in Brazil and Russia.

Cheng et al. (2019) investigated the impacts of renewable energy, environmental patents, economic growth, exports of goods and services, foreign direct investment, and domestic credit to the private sector on the carbon emission per capita from 2000 to 2013, using both the panel OLS methods and panel quantile regression method. They found that the effects of determinant variables were heterogeneous across quantiles. Dong et al. (2017) employed a panel VECM to investigate the nexus among per capita carbon dioxide (CO_2) emissions, gross domestic product (GDP), and natural gas and renewable energy consumption within the framework of the environmental Kuznets curve (EKC) during the period of 1985–2016 of BRICS countries. The results provided strong evidence in favor of the EKC hypothesis for the BRICS countries by proposing that the EKC hypothesis held in all five BRICS countries.

Nassani et al. (2017) researched the EKC hypothesis using finance, transport, energy, and growth specific factors on different environmental pollutants in a panel of BRICS countries during the period of 1990–2015. The results showed that the EKC hypothesis was valid in BRICS countries. Azevodo et al. (2018) examined the relationship between the volume of carbon dioxide emissions by lag of the emissions and the Gross Domestic Product, dividing the BRICS countries into two groups from 1980-2011, and they found that the relationship between economic growth and CO_2 emissions was not the same for all countries. Sinha et al. (2019) presented the impact of corruption in the public sector on environmental quality for BRICS and Next 11 countries for the period of 1990-2017, and they found an inverted N-shaped Environmental Kuznets Curves.

3. Model and Data

The main objective of the current study is to investigate the relationship between CO_2 emissions, economic growth, and energy consumption for BRICS countries by using annual data over the period of 1971-2013 and, in this context, to examine the validity of the EKC hypothesis. For this purpose, following the empirical literature in energy economics, the general functional form of the model is constructed as follows:

$$CO_2 = (GDP, GDP^2, EC) \tag{1}$$

where CO_2 represents the per capita CO_2 emissions, *GDP* represents the per capita real *GDP*, and *EC* represents per capita energy consumption. Since the pollution will increase with revenue up to a threshold and then begin to decrease, the model specification of Eq (1) follows an inverted-U relationship between CO_2 and *GDP*. The empirical equation is a quadratic form as suggested by Grossman and Krueger (1991) and is formulated as follows:

$$\ln CO_{2it} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 (\ln GDP_{it})^2 + \beta_3 (\ln EC_{it}) + u_{it} \tag{2}$$

where i indicates the country samples (i=1,2,..., N), t indicates the time span (t=1,2,...,T), u_{it} is the error term with $Cov(u_{it}, u_{jt}) = 0$ for $i \neq j$. β_0, β_1, β_2 and β_3 are the coefficients to be estimated. In Eq. 2, ln *GDP* and (ln *GDP*)^2 refer to the *EKC* hypothesis, where there is a nonlinear quadratic relationship between income and environment pollutants. Following the EKC insight (pollution increases with income, up to a threshold point, then starts decreasing), β_1 and β_2 are expected to be positive and negative, respectively, energy consumption is to increase the emission of CO_2, and β_3 is expected to be positive.

In this study, per capita CO_2 emissions are in metric tons of carbon dioxide, per capita real *GDP* is measured in billion US dollars at 2010 prices, per capita energy consumption (*EC*) is measured in kg of oil equivalent. The data was obtained from the World Bank Data, World Development Indicators (WDI).

Table 2
Summary statistics for CO_2 *Emissions, Energy Consumption and Real GDP of the BRICS countries between 1971-2014 (before taking logarithm)*

	CO_2 Emissions		**Energy Consumption**		**Real GDP**	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Brazil	1.907	0.300	1164.821	165.368	9634.455	1348.914
China	4.346	1.918	1328.759	528.323	2803.480	1633.993
India	1.117	0.287	462.265	85.050	1007.819	320.000
Russia	11.484	0.953	4594.582	384.886	8415.077	2237.287
South Africa	8.802	0.599	2581.743	167.138	6491.600	786.498

Table 2 provides a statistical summary associated with the actual values of three variables (CO_2, *GDP*, *EC*) for the five BRICS countries. As can be seen, the highest means of per capita CO_2 emissions (11.484) and per capita energy consumption (4594.582) are both found in Russia. On the other hand, Brazil having the highest real GDP per capita mean (9634.455). The lowest means of per capita emissions (1.117), per capita energy consumption (462.265) and per capita real GDP (1007.819) are found in India. Additionally, China displays the greatest variation (defined by the standard deviation) in per capita emissions (1.918) and energy use (528.323).; Russia has the highest variation in real GDP (2237.287) while India exhibits the least variation in each variable.

3. Econometric Methodology

3.1. Panel Unit Root Tests

The precondition when testing a cointegration relationship among the variables is the existence of a unit root in related variables. There are a large number of panel unit root tests available in the literature. The group of panel unit root tests that are defined as *first-generation panel unit root tests* does not consider the presence of cross-sectional dependence among the members of the panel. These kinds of tests can be subdivided into two groups as homogeneous and heterogeneous cases. The homogeneous panel unit root test postulates homogeneous autoregressive coefficients between individuals. The panel unit root test of Levin et al. (2002) (LLC) falls into this group. The assumption that autoregressive coefficients are identical across the panel is very restrictive since it is not acceptable that the stationarity characteristics for all series of a variable are the same for all individuals in a panel. This limitation is overcome by the heterogeneous panel unit root tests, allowing the autoregressive coefficients to differ across the panel. The panel unit root tests introduced by Im et al. (2003) (IPS) and Maddala and Wu (1999) fall into this group.

The *second-generation panel unit root tests* assume cross-sectional dependence among the panel members. The presence of dependence across the panel can possibly be due to several factors such as economic linkages from common global shocks, spatial spillover effects, or unobserved common factors (Baltagi and Pesaran, 2007).

As well as the LLC, IPS, and Maddala-Wu panel unit root tests, this study also employs the cross-sectional augmented IPS (CIPS) panel unit root test of Pesaran (2007), which considers both heterogeneity and cross sectional-dependence.

3.1.1. Levin, Lim and Chu (LLC) Test

The LLC panel unit root test based on the ADF (Augmented Dickey-Fuller) test allows for homogeneity in the dynamics of the autoregressive coefficients for all panel units with cross-sectional independence. LLC unit root test considers the following panel ADF specification to test the presence of a unit root.

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{i,j} \Delta y_{i,t-j} + e_{i,t} \tag{3}$$

where Δ denotes the first difference operator. $y_{i,t}$ is a vector and represents the variables that are ln CO_2, ln *GDP*, (ln *GDP*)^2 and ln *EC* tested for unit root. α_i, β and $\gamma_{i,j}$ are the coefficients to be estimated. $e_{i,t}$ is independently and normally distributed random variable for all i and t with zero means and finite heterogeneous variances, $e_{i,t}$: $\sim IID(0,\sigma_i^2)$. p_i is the number of lags selected for the ADF regression and is unknown.

The LLC test assumes that the persistence parameters β_i of the lagged dependent variable is homogeneous (identical) for all individuals of the cross-sections of the panel (i.e., $\beta_i = \beta$ for all i) while the lag order β_i may freely vary. Thus, the hypotheses tests for the LLC panel unit root testing are formulated as follows:

$$H_0 : \beta_1 = \beta_2 = \cdots \beta_{\mathrm{i}} = \beta = 0$$

$$H_0 : \beta_1 = \beta_2 = \cdots \beta_{\mathrm{i}} = \beta < 0$$

The hypothesis test is $H_0 : \beta = 0$ for existence of unit root whereas $H_1 : \beta < 0$ for all i for the non-existence of a unit root. The hypothesis structure in the LLC unit root test is close to the one proposed by Dickey and Fuller. As p_i is unknown, the LLC testing procedure is implemented in three-steps.

In the first step, the ADF regression for each individual i in the panel is estimated and orthogonal residuals are generated. In the second step, an estimation of the ratio of long-run to short-run deviation for each individual is required. In the third and final step, the pooled t –statistics are computed.

The independence assumption of individuals' errors ($e_{i,t}$) implies the use of a central limit theorem. Therefore, statistical tests are asymptotically normally distributed, and the conventional t-statistic regression to the test $\beta = 0$ is as follows:

$$t_{\hat{\beta}_i} = \frac{\hat{\beta}}{Se\left(\hat{\beta}\right)} \tag{4}$$

where $\hat{\beta}$ is the OLS estimate of β_i, which is the same for all individuals in Eq. (3) and Se ($\hat{\beta}$) is its standard error. Although the LLC test is widely used as a panel root test, as mentioned above, the test has a homogeneity limitation.

3.1.2. Im-Pesaran and Shin (IPS) test

Im et al (2003) proposed their panel unit root test, which is also based on Eq (3) and is an extension of the LLC test, in order to test the presence of a unit root. Unlike the LLC test, the IPS test allows for heterogeneity of the first-order autoregressive parameters for all panel members, but the cross-sectional independence assumption is still valid. The IPS test is based on the following Augmented Dickey-Fuller (ADF) regression:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \sum_{j=1}^{p_i} \theta_{ij} \Delta y_{it-j} + e_{it} \tag{5}$$

The hypothesis test is defined as follows:

$$H_0 : \beta_i = 0 \quad \text{for} \quad i = 1,\ldots,N$$

$$H_1 : \begin{cases} \beta_i < 0 & \text{for} \quad i = 1,\ldots,N_1 \\ \beta_i = 0 & \text{for} \quad i = N_1 + 1, N_1 + 2,\ldots,N \end{cases}$$

As mentioned above, this formulation of the alternative hypothesis allows for β_i to differ across groups and is more general than the homogeneous alternative hypothesis, namely $\beta_i = \beta$ < 0 for all i. In other words, the alternative hypothesis allows unit roots for some of the individual series. More specifically, while N_1 series are stationary, $N - N_1$ series contain unit roots.

After estimating ADF regressions separately for each country, the average of the t-bar statistics for β_i is calculated from the individual ADF regressions and is as follows:

$$t - \text{bar}_{NT} = N^{-1} \sum_{i=1}^{N} t_{iT}\left(\beta_i, \theta_i\right) \tag{6}$$

where $t_{iT}(\beta_i,\theta_i)$ is the individual t-statistics for testing $\beta_i = 0$ for all i. To test the hypothesis, Im et al. (1997) purposed a standardized t-bar statistic ($Z_{t\text{-}bar}$) that is based on the theoretical means - $E[t_{iT}(\beta_i,\theta_i)]$ - and variances - $Var[t_{iT}(\beta_i,\theta_i)]$ - of $t_{iT}(\beta_i,\theta_i)$, which is as follows:

$$Z_{t-\text{bar}} = \frac{\sqrt{N}\left\{t-\text{bar}_{NT} - N^{-1}\sum_{i=1}^{N} E\left[t_{iT}\left(p_i,0\right)\middle|\beta_i=0\right]\right\}}{\sqrt{N^{-1}\sum_{i=1}^{N} Var\left[t_{iT}\left(p_i,0\right)\middle|\beta_i=0\right]}} \Rightarrow N\left(0,1\right) \tag{7}$$

Im et al. (2003) showed that the standardized t-bar statistic ($Z_{t\text{-}bar}$) is asymptotically distributed as a standard normal distribution [$Z_{t\text{-}bar} \Rightarrow N(0,1)$] under the null hypothesis that $\beta_i = 0$ for all i. Im et al. (2003) presents the critical values for various combinations of N and T based on Monte Carlo simulations of $E[t_{iT}(\beta_i,\theta_i)]$ and $Var[t_{iT}(\beta_i,\theta_i)]$ with 50,000 replications at conventional significance levels.

Breitung (1999) found that the IPS suffered a dramatic loss of power when individual trends were included, and the test was sensitive to the specification of deterministic trends.

3.1.3. Maddala and Wu Test

Maddala and Wu (1999) purposed a panel unit test that is based on Fisher (1932). This test, also known as Fisher's test (1932), is non-parametric and straight-forward to use. The Maddala and Wu panel unit root test is essentially based on combining the p-values of the test statistics (of β_i) of the N independent ADF regressions from Eq. (5). According to Maddala and Wu, if the test statistics are continuous, the significance levels π_i ($i = 1,\ldots,N$) are independent and uniform (0,1) variables.

The test statistic using the additive property of the chi-squared variable is as follows:

$$\lambda = -2\sum_{i=1}^{N} \log_e \pi_i \rightarrow \chi^2_{2N} \tag{8}$$

The test has a chi-square distribution with $2N$ degrees of freedom as $T \rightarrow \infty$ and N is fixed under the null hypothesis, where N is the number of cross-sectional units and π_i represents the p-values from individual ADF tests. Obviously, the Maddala and Wu unit root test essentially combines the p-values of the test statistic for the unit root in each residual cross-sectional unit.

Similar to the IPS test, this test allows for different first–order autoregressive coefficients and has the same null and alternative hypotheses in the estimation procedure, but this test, which can use different lag lengths in the individual ADF regressions, has an important advantage over the IPS test, which must use the same lag length. Therefore, the Maddala and

Wu test may decrease the bias that is caused by the lag selection (Banerjee 1999, Maddala and Wu 1999). The Maddala and Wu test does not require a balanced panel. Maddala and Wu (1999) found that the MW test is superior compared to the IPS test. Another important advantage of this test is that it can be used regardless of whether the null hypothesis is one of integration on stationarity.

The disadvantage of the test is that the *p*-values have to be derived by Monte Carlo simulation.

3.2. Tests for cross section dependence

A serious drawback of conventional panel unit root tests (first-generation) discussed above is the assumption that individuals are cross-section independent (CD). However, the assumption of independence is often not valid in the use of macroeconomic indicators because the countries are interlinked with each other at the regional and global levels. If the cross-sectional dependence is not controlled, then the estimators will be inconsistent and biased (Phillips and Sul, 2003). Also, O' Connell (1998) pointed out that the failure to consider contemporaneous correlations among data will skew the panel-based unit root test towards rejecting the joint unit root hypothesis. Since ignoring the CD in the estimation will lead to a loss in efficiency and invalid statistics, econometric modelling in a panel context does require accounting for the cross-section dependence phenomenon.

To check for the potential presence of CD among the individuals used in this study, we implemented four different tests; which are the Breusch-Pagan Lagrange multiplier (LM) test, developed by Breusch and Pagan (1980); the scaled LM suggested by Pesaran (2004); the Pesaran CD test, proposed by Pesaran (2004); and the bias-adjusted LM test developed by Pesaran et al. (2008).

Breusch and Pagan (1980) proposed the Lagrange multiplier (LM) test statistic which is calculated from estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i^{'} x_{it} + u_{it} \qquad i = 1, 2, \ldots, N \qquad t = 1, 2, \ldots, T \tag{9}$$

where x_{it} is $k \times 1$ vector of explanatory variables and α_i and β_i are the individual intercepts and slope coefficients that are allowed to vary across individual, respectively. In the Breusch – Pagan LM test, the null hypothesis of no cross-section dependence is tested against the alternative hypothesis of cross section dependence and can be written as follows:

$$H_0 : \rho_{ij} = \rho_{ji} = Cov\left(u_{it}, u_{jt}\right) = 0 \quad \text{for all } t \text{ and } i \neq j$$

$$H_1 : \rho_{ij} \neq \rho_{ji} \neq Cov\left(u_{it}, u_{jt}\right) \neq 0 \quad \text{for at least one pair of } i \neq j$$

Breusch – Pagan LM test can be expressed as follows:

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \sim \chi^2_{N(N-1)/2} \tag{10}$$

where T_{ij} is the number of observations for which the correlation coefficient was computed and N is the number of groups in the panel. $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation coefficients among the residuals obtained from the individual ordinary least squares (OLS) estimation of Eq (9) for each individual series and is as such:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\hat{u}_{jt}}{\left(\sum_{t=1}^{T}\hat{u}_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T}\hat{u}_{jt}^2\right)^{1/2}}$$

Under the null hypothesis, the LM statistic has a chi-square asymptotically distributed with $N(N\text{-}1)/2$ degrees of freedom. The Breusch-Pagan LM test is valid for N relatively small and T sufficiently large.

Pesaran (2004) stated that Breusch-Pagan LM test is not appropriate for large panels N. In order to deal with this problem, Pesaran (2004) proposes a standardized version of the LM test known as the Scaled LM test for large panels, where $T \rightarrow \infty$ first and then $N \rightarrow \infty$. The Scaled version of the LM test is as follows:

$$LM_{sc} = \sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\hat{\rho}_{ij}^2 - 1\right) \sim N(0,1) \tag{11}$$

Under the null hypothesis of no cross-sectional dependence, the test is asymptotically distributed as standard normal, but the Scaled LM test also suffers from size distortion for small time dimension (T) with the distortion worsening if N increases.

To overcome this matter, Pesaran (2004) developed a test for panels where $T \rightarrow \infty$ and $N \rightarrow \infty$ in any order. This test is a simple test of error CD based on the average of pair-wise correlation coefficients ($\hat{\rho}_{ij}$) of the OLS residuals that were obtained from the standard augmented Dickey-Fuller (1979). Pesaran's test has good performance in small samples and is also applicable for dynamic heterogeneous panels. Pesaran CD test can be given as:

$$CD = \sqrt{\frac{2T}{N(N-1))}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \sim N(0,1) \tag{12}$$

CD statistic tests under the null of cross-sectional independence is distributed as a two-tailed standard normal distribution for $T_{ij} > 3$ and sufficiently large N.

However, Pesaran et al. (2008) stated that the CD test would lack power in certain situations where the population average pair-wise correlations are zero although the underlying individual population pairwise correlations are non-zero. Additionally, in stationary dynamic panel data models, the CD test fails to reject the null hypothesis when the factor loadings have zero mean in the cross-sectional dimension. In order to control size distortion in the Scaled LM test and to eliminate the above-mentioned disadvantages, Pesaran (2004) suggested an alternative test statistic that is a bias-adjusted test based on the average of the pairwise correlation coefficients for large panels where $T \rightarrow \infty$ first and then $N \rightarrow \infty$.

The bias-adjusted test, which is a modified version of the LM test suggested by Pesaran et al., is based on the use of the exact mean and variance of the LM statistics. The bias-adjusted LM test can be calculated as follows:

$$LM_{adj} = \sqrt{\frac{2}{N(N-1))}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\frac{(T-k)\hat{\rho}_{ij}^{2}-\mu_{Tij}}{\sqrt{v_{Tij}^{2}}}\right) \sim N(0,1) \tag{13}$$

where k is the number of regressors and μ_{Tij} and v_{Tij}^2 are the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, respectively, all of which were provided in Pesaran et al. (2008). Under the null hypothesis where $T \rightarrow \infty$ first and then $N \rightarrow \infty$, the LM_{adj} test is asymptotically distributed as standard normal.

3.2.1. CIPS Panel Unit Root Test

As mentioned above, in the case of cross-sectional dependence across individuals in the panel, first-generation conventional panel unit root tests, which tend to suffer from size distortions and skew the tests toward the alternative hypothesis, are not applied. To address this shortcoming, Pesaran (2007) suggested taking into account the presence of cross-sectional dependence in order to produce reliable estimates through the use of a new second-generation panel unit root test. Pesaran's test is a modified IPS statistics (CIPS) which is based on the cross-sectional augmented ADF statistics (denoted as CADF) and is referred to as a second-generation unit root. The computation of the CADF regression is as follows:.

$$\Delta y_{it} = a_i + b_i y_{it-1} + c_i \overline{y}_{t-1} + d_i \Delta \overline{y}_t + e_{it} \tag{14}$$

where y_{it} could represent all variables, including ln CO_2, ln GDP, (ln GDP)^2, and ln EC. a_i, b_i, c_i, and d_i are slope coefficients estimated from the ADF test in country i. $\overline{y}_{t-1}$ is the mean value of lagged value $\overline{y}_{t-1} = N^{-1}\sum_{j=1}^{N} y_{it-1}$, and $\Delta\overline{y}_t$ is the mean value of first differences $\Delta\overline{y}_t = N^{-1}\sum_{j=1}^{N}\Delta y_{it}$. e_{it} is error term. The reason for adding the cross-sectional mean of y_{it} is to proxy the common factor. Pesaran augments the ADF regressions with the cross-section averages of lagged levels ($\overline{y}_{t-1}$) and first differences ($\Delta\overline{y}_t$) for each unit. The optimal lag-length is selected by Akaike Information Criterion (AIC) or the Schwarz-Bayesian Information Criterion (SBC). For the CIPS panel unit root test, the null hypothesis expressing the unit root ($b_i = 0$ for all i.) is tested against the alternative hypothesis ($b < 0$) that expresses stationarity. After running the CADF statistics, the CIPS statistic can be represented as follows:

$$CIPS(N,T) = \frac{1}{N}\sum_{i=1}^{N} t_i(N,T) \tag{15}$$

where $t_i(N,T)$ indicates the t-statistic of $\beta_i = 0$ for the i, the individual in the CADF regression defined by Eq. (14). The latter does not allow the normal distribution, but simulated critical values are tabulated in Pesaran (2007).

3.3. Panel Cointegration Tests

If there are unit roots in the series, then in the next step, the panel cointegration test is applied to examine whether individual series are linked to form an equilibrium relationship spanning in the long-run. As in the panel unit root tests, the panel cointegration methods are used to increase the power of conventional cointegration analysis for pure time series. In the literature, different panel cointegration tests such as Pedroni (1999), Pedroni (2004), and Kao (1999), which are all Fisher-type tests, known as the first generation of panel cointegration, are widely used, but, they consider the independence of cross-section. To deal with this, in addition to the Kao panel cointegration test, the newly developed Westerlund-Edgerton (2008) test is used, which allows for the cross-section dependence by means of bootstrap methods in this paper.

3.3.1. Kao Panel Cointegration Test

Kao (1999) proposed a methodology to test the panel data cointegration that can be considered as an extension of the traditional Engle-Granger (1987) two-step procedure. The Kao cointegration test is similar to that of Pedroni (1999), but Kao (1999) specifies cross-section specific intercepts and homogeneous coefficients on the first stage regressors. This test considers the following system of cointegrated regressions:

$$y_{it} = \alpha_i + x_{it}\beta + u_{it} \tag{15}$$

$$x_{it} = x_{it-1} + \varepsilon_{it} \tag{16}$$

where α_i is individual constant terms, β is the slope parameter that Kao (1999) indicates as the assumptions of the co-integrating vector from Eq. (16) with $\beta_{\mathrm{i}} = \beta$. Therefore, the panels follow common slope coefficients. u_{it} is a stationary error term, and y_{it} and x_{it} are integrated processes of order one for all i.

The Kao (1999) cointegration test is a residual-based cointegration test. Kao tests the residual $\hat{u}_{it}$ of the OLS panel estimation by applying the Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests. Both tests are calculated from:

$$\hat{u}_{it} = \rho \hat{u}_{it-1} + \sum_{j=1}^{p} \phi_j \Delta \hat{u}_{it-j} + v_{it} \tag{17}$$

where the residuals $\hat{u}_{it}$ are obtained from Eq (16). The null hypothesis of no cointegration, $H_0 : \rho = 1$, is tested against the alternative hypothesis of stationary residuals, $H_1 : \rho < 1$. Kao (1999) assumed, for the null and alternatives hypotheses, that either all the relationships are not cointegrated or all the relationships are cointegrated. Kao proposed five DF and ADF types of cointegration tests in the panel data, the asymptotic distributions of which converge to a standard normal distribution $N(0,1)$ as $T \rightarrow \infty$ and $N \rightarrow \infty$. The test statistics are DF_{γ}^{*}, DF_{t}^{*}, and ADF, which are for cointegration with the endogenous regressors, and DF_{γ} and DF_t, which are based on the assumption of the strict endogeneity of the regressors. As mentioned above, all five versions of Kao's test impose homogeneity in the slope coefficient β, which is not allowed to vary across the i individual members of the panel. In this study, the null of cointegration is tested using the ADF test.

3.3.2. Westerlund and Edgerton Panel Cointegration Test

In addition to Kao's test, Westerlund and Edgerton (2008) panel cointegration test is used in this study. This test has several advantages over the first generation of panel cointegration. The Westerlund and Edgerton (2008) panel cointegration test, which allows both the accommodation of cross-sectional dependence and structural breaks (in the slope and/or intercept of the cointegrating relationship) simultaneously. The Westerlund and Edgerton (2008) panel cointegration test is known as second-generation cointegration tests because this test takes into consideration heteroskedastic, serially correlated errors and cross-unit specific time terms.

The bootstrap panel cointegration test proposed by Westerlund and Edgerton (2007) is based on the Lagrange multiplier (LM) test of McCoskey and Kao (1998) but allows dependence both within and between the individual cross-section units.

Westerlund and Edgerton (2008) consider the following model:

$$y_{it} = \alpha_i + \eta_i t + \delta_i D_{it} + x_{it}^{'} \beta_i + (D_{it} x_{it})^{'} \gamma_i + z_{it} \tag{18}$$

$$x_{it} = x_{it-1} + w_{it}$$

where i (i=1,2,..., N) and t (t=1,2,...,T) denote the indexes of time and cross-section units, respectively. x_{it} is a k-dimensional vector containing the variables and is modelled as a pure random walk. α_i and β_i represent the intercept and slope before the break while δ_i and γ_i represent the change in these parameters at the time of the shift. w_{it} is an error process with mean zero and is independent across i. z_{it} is an error term and is generated by the following model:

$$z_{it} = \lambda_i^{'} F_t + v_{it} \tag{19}$$

$$F_{jt} = \rho_j F_{jt-1} + u_{jt} \tag{20}$$

$$\Delta v_{it} = \phi_i v_{it-1} + \sum_{j=1}^{p} \phi_{ji} \Delta v_{it-j} + e_{it} \tag{21}$$

where j is the common factors dimension (j=1,2,...,K). v_{it}, u_{jt}, and e_{it} are error terms with mean zero stationary processes, which are identically and distributed cross-sectionally. The e_{it} and w_{it} are independent for i and t. The variable D_{it} is a scalar break dummy variable defined as follows:

$$D_{it} \begin{cases} 1 & \text{if } t > T_i^b \\ 0 & \text{otherwise} \end{cases}$$

where $T_i^b = \lambda_i^b T$ and $\lambda_i^b \in [n, n-1], n \in (0,1)$. The hypothesis to be tested is $H_0 : \phi_i = 0$ for all vs. $H_1 : \phi_i < 0$ for at least some i. If $\phi_i < 0$, the relationship in Eq. (2) is cointegrated, and if $\phi_i = 0$, it is spurious.

The proposed test statistics for the cointegration test are as follows.

$$\overline{LM}_{\phi}(N) = \frac{1}{N} \sum_{i=1}^{N} LM_{\phi}(i) \tag{22}$$

$$\overline{LM}_{\tau}(N) = \frac{1}{N} \sum_{i=1}^{N} LM_{\tau}(i) \tag{23}$$

where $LM_{\phi}(i) = T\hat{\phi}_i \left(\hat{W} / \hat{\sigma}_i \right)$ and $LM_{\tau}(i) = \hat{\phi}_i / SE(\hat{\phi}_i)$. $\hat{\phi}$ is the OLS estimates of ϕ in Eq. (21), $SE(\hat{\phi})$ is its standard error and $\hat{\sigma}_i = \sqrt{1 / T \sum_{t=1}^{T} e_{it}^2}$.

Westerlund and Edgerton (2008) drive two statistics under the null hypothesis of no cointegration. The normalized test statistics obtained by taking into account the asymptotic properties of the $LM_{\phi}(i)$ and $LM_{\pi}(i)$ statistics are as follows:

$$Z_{\phi}(N) = \sqrt{N}(\overline{LM}_{\phi}(N) - E(\mathrm{B}_{\phi})) \tag{24}$$

$$Z_{\tau}(N) = \sqrt{N}(\overline{LM}_{\tau}(N) - E(\mathrm{B}_{\tau})) \tag{25}$$

The test statistics are normally distributed and have good small-sample properties. This test can be used in cases of the existence and cases of the nonexistence of cross-sectional dependency.

3.4. Panel Fully Modified OLS (FMOLS)

After determining the cointegration relationship between variables, one must next estimate the long-run parameters (i.e., the cointegration coefficients of independent variables). Since the ordinary least squares (OLS) estimator is asymptotically biased and its distribution depends on nuisance parameters (in the context of a panel estimate), the long run association among the variables is examined by using the panel fully modified ordinary least square (FMOLS) technique. The FMOLS technique, which was proposed by Phillips and Hansen (1990) and later modified by Pedroni (2000), is highly effective in addressing the series correlation between endogeneity and error correlations between regressors. For the problems of endogeneity and serial correlation, the FMOLS method uses a non-parametric approach. The FMOLS estimator produces asymptotically unbiased estimates of the long-run elasticities and efficient, normally distributed standard errors.

The FMOLS estimation method provide the most reasonable estimators in a panel regression model as follows:

$$y_{it} = \alpha_i + \beta x_{it} + u_{it}$$

where y_{it} are 1x1, α_i are the intercepts, β is a kx1 vector of the slope parameters, and u_{it} are the stationary disturbance terms. x_{it} are the kx1 integrated process of the one for all i ($x_{it} = x_{it-1} + \varepsilon_{it}$). Under these assumptions, the panel FMOLS model can be written as:

$$\hat{\beta}_{FMOLS} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} \left(x_{it} - \overline{x}_i \right) \left(x_{it} - \overline{x}_i \right)' \right]^{-1} \left[\sum_{i=1}^{N} \left(\sum_{t=1}^{T} \left(x_{it} - \overline{x}_i \right) \hat{y}_{it}^{+} - T \hat{\Delta}_{eu}^{+} \right) \right] \tag{26}$$

where $\hat{y}_{it}^{+}$ is the y_{it} series corrected for endogeneity, and $\hat{\Delta}_{eu}^{+}$ represents the correction term, assuming serial correlation term (between u_{it} and an error term ε_{it}).

4. Empirical Results

The aim of this paper is to test a long run relationship between economic growth, energy consumption, and carbon emissions in BRICS countries, using the data for the 1971-2013 period and is to test the validity of the EKC hypothesis in this context. In the first step, three different statistics (LLC, IPS, and Maddala-Wu) from the first-generation panel unit root tests described above will be applied to determine the stationarity levels of the variables and to determine which econometric technique will be used to test the possible relationship between the variables. The results of the LLC, IPS, and Maddala-Wu panel unit root tests for each of the variables are shown in Table 3.

Table 3
Results of First-Generation Panel Unit Root Tests

LLC Panel Unit Root Test		
	Level	**First Differences**
ln CO_2	0.5368 (0.7043)	-4.53567 (0.0000)
ln GDP	0.338 (0.6323)	-4.40968 (0.0000)
$(\ln GDP)^2$	1.0299 (0.8485)	-4.2816 (0.0000)
ln EC	1.4957 (0.9326)	-5.6158 (0.0000)
IPS Panel Unit Root Test		
	Level	First Differences
ln CO_2	1.4438 (0.9256)	-3.96533 (0.0000)
ln GDP	2.57893 (0.995)	-4.44136 (0.0000)
$(\ln GDP)^2$	3.08768 (0.999)	-4.21411 (0.0000)
ln EC	2.82726 (0.9977)	-5.16674 (0.0000)
Maddala-Wu Panel Unit Root Test		
	Level	First Differences
ln CO_2	8.88615 (0.5429)	36.1297 (0.0000)
ln GDP	3.40531 (0.9702)	45.831 (0.0000)
$(\ln GDP)^2$	3.07168 (0.9797)	37.938 (0.0000)
ln EC	4.9638 (0.8936)	36.2828 (0.0001)
Note: Numbers in parentheses show the p-values.		

The results of all panel unit root tests show that the variables of interest are stationary at the first level. However, an important deficiency of these tests is that they do not consider possible cross-sectional dependence among the panel members. However, BRICS countries are highly integrated and have a high degree of globalization in economic relations. Therefore, one important issue is to take into account cross-sectional dependence in this empirical analysis based on the BRICS countries data. To determine whether the cross-section dependence exists or not, four different tests were applied, and the results are illustrated in Table 4.

Table 4
Cross sectional dependence

	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
ln CO_2	83.2909 (0.0000)	16.38834 (0.0000)	16.2747 (0.0000)	7.5273 (0.0000)
ln EC	124.7474 (0.0000)	25.65831 (0.0000)	25.5447 (0.0000)	10.5776 (0.0000)
ln GDP	207.6017 (0.0000)	44.18508 (0.0000)	44.0714 (0.0000)	14.3953 (0.0000)
$(\ln GDP)^2$	208.7296 (0.0000)	44.43728 (0.0000)	44.3236 (0.0000)	14.4359 (0.0000)
Note: Numbers in parentheses show the p-values.				

The null hypothesis of cross-sectional independence for each variable is rejected for all the tests, according to the results in Table 4. Under the presence of cross-sectional dependence, the result from the LLC, IPS and Maddala-Wu tests might be biased and misleading. Wherefore the cross-sections are significantly dependent on each other, we must consider this dependence and use tests that allow for the dependence. Thus, in the next step, the CIPS panel unit root test, introduced by Pesaran (2007) and is the second-generation panel unit root test, was used, with the results being reported in Table 5.

Table 5
Results of CIPS test

Variables	Level	First Differences
ln CO_2	-2.493	-3.215*
ln GDP	-2.408	-3.421*
$(\ln GDP)^2$	-2.555	-3.123*
ln EC	-2.684	-3.278*
Note: *shows the statistical significance.		

The results of CIPS panel unit root test are shown in Table 5. All the variables were differenced-stationary since test statistics are lower than the critical value at the 10% level. On balance, the results of 5 demonstrate that all of the series in Eq. (2) appear to contain a panel unit root in their levels but are stationary in their first differences, indicating that they are integrated at order one, i.e., $I(1)$. Since each of the four variables in the panel is I(1), the system can be tested for cointegration. The Westerlund-Edgerton (2007) panel cointegration test results, which allows structural breaks and also considers cross-sectional dependence, are illustrated in Table 6. We also employed the Panel Kao cointegration test to examine the existence of the long run equilibrium for comparison purposes:

Table 6
Results of Panel Cointegration Test

Test	**Test Statistics**
Panel Kao	-4.603465 (0.0000)
Westerlund-Edgerton	4.3832 (0.0000)
Note: Numbers in parentheses show the p-values.	

The results of the Kao test, which is widely used in the literature, show that the null hypothesis of no cointegration at the 1% significance level is rejected. In addition, the Westerlund-Edgerton (2007) cointegration results reported in Table 6 also display that the statistics reject the null of no cointegration at the 1% significance level; thus, the cointegration relationship is further confirmed by the Westerlund-Edgerton (2007) test. This reveals that there is a long-run cointegrating relationship between CO_2 emission and its determinants for BRICS countries during the period of 1971–2013

After the presence of a cointegration relationship is confirmed, to see the size of the coefficients of the long-run model, the long-run cointegration vector is estimated by using the Fully Modified OLS (FMOLS). Table 5 shows the long–run estimation results with carbon emissions being the dependent variable.

Table 7
Estimation Results of Panel FMOLS

Variable	**Coefficient**
ln EC	1.185342 (0.0000)
ln GDP	0.716999 (0.0000)
$(\ln GDP)^2$	-0.047572 (0.0000)
Note: Numbers in parentheses show the p-values.	

The sign of coefficients of ln EC, LnGDP, and $(\text{Ln GDP})^2$ are positive, positive, and negative, respectively, and all the variables are statistically significant at conventional levels. Because the variables take place in the model with their logarithmic values, the coefficients can be interpreted as elastic. Thus, we can interpret the coefficients as follows: a 1% increase in ENG, and GDP creates a 1.18%, and 0.72% increases in CO_2, but a 1% increase in GDP^2 decreases CO_2 by 0.04%. These results provide evidence supporting an inverted U-shaped relationship among CO2 emissions and economic activities. Thus, the Environmental Kuznets Curve hypothesis is supported by the panel of BRICS countries. The FMOLS results in Table 7 also show that energy consumption has a significantly detrimental effect on the environment.

5. Conclusion

In this study, we investigated the impact of economic growth and energy consumption on carbon emissions for the BRICS countries over the period of 1971-2013 using panel cointegration techniques that allow for cross-section dependence and structural breaks. For this purpose, the stationary levels of the variables were first examined by unit root tests which did not take into account cross-sectional dependence. The results show that the variables are stationary in the first differences. The presence of cross-sectional dependence in the variables was investigated, and it was concluded that there was cross-sectional dependence in the variables. For this reason, the stationarity of the variables was examined using unit root tests considering cross-sectional dependence, and it was determined that the variables were stationary in the first differences. The long-run relationship between the variables was examined using two different cointegration tests. According to the results of both tests, a long-term relationship was found between the variables. The coefficients of the long-run relationship were estimated by the Panel FMOLS method. The results for long-run coefficient estimation are as follows: a 1% increase in energy consumption, and GDP creates a 1.18%, and 0.72% increases in CO_2, but 1% increase in GDP^2 decreases CO_2 by 0.04%. The main results of this paper on the panel of BRICS countries is that an inverted U-shaped environmental Kuznets curve hypothesis is supported, and there is a significant detrimental effect of energy consumption on the environment

The results of the study provide guidance for policy makers in BRICS countries. According to these results, economic growth and energy consumption are important determinants of environmental pollution in BRICS economies. Therefore, as increasing energy consumption will lead to more pollution in the long term, policy makers need to encourage alternative energy sources to meet increasing energy demands. Increasing the CO_2 emissions indicate that energy consumption based on fossil fuels should be reduced through diversifying policies of energy resources. Moreover, in order to prevent climate change, policy makers should focus on green growth rather than economic growth. Green growth will also positively affect economic growth.

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